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Evaluating the Influence of La Niña on Tropical Greening in Borneo Through Geographically Weighted Regression

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Abstract **–** This study evaluates the influence of the 2007 strong La Niña event on tropical greening in Borneo by using geographically weighted regression (GWR) to assess spatial variations in vegetation response based on remotely sensed NDVI data. Moran's I value, ranging from 0.012 to 0.034, indicates low positive spatial autocorrelation and significant spatial clustering of rainfall across Borneo, underscoring the importance of incorporating spatial factors in the analysis. The ANOVA test shows that each monthly GWR model significantly outperforms the Ordinary Least Squares (OLS) model ($F > 1$, $p < 0.05$), with September, October, and December exhibiting the strongest fit (Quasi-global R^2: 0.2744, 0.3125, 0.2899; RSS: 0.2626, 0.2539, 0.2785). During the Northeast Monsoon (NEM), the rainfall-NDVI relationship is strongest, with maximum R^2 values peaking at 0.74 in December, followed by 0.54 in February and 0.27 in November. Central and southern Borneo show the highest correlations, indicating that rainfall is a key driver of vegetation growth. During the Southwest Monsoon (SWM), the rainfall-NDVI relationship weakens, with maximum R^2 dropping to 0.36 in August before rising to 0.49 in September. The lowest R^2 (0.00–0.04) in northern and eastern Borneo reflects reduced rainfall influence due to orographic rain shadow effects from the Crocker Range and East Kalimantan highlands. Western Borneo's peatlands and riparian zones retain moisture and sustain vegetation, while degraded forests, mixed land use, and plantations in the north and east show more significant NDVI fluctuations due to lower soil moisture retention. The predicted NDVI values during the 2007 La Niña event ranged from 0.5 to 0.9, with the model effectively capturing seasonal and spatial variations across Borneo, particularly during peak rainfall. However, it missed localized fluctuations and smaller-scale variations in February and November due to elevation, soil and vegetation type, and extreme rainfall variability. These findings suggest that local factors mediate La Niña's influence on tropical greening, emphasizing the importance of spatial analysis in understanding climate-vegetation interactions under extreme conditions.

Keywords – *Borneo, CMORPH, ENSO, Geographically Weighted Regression, NDVI, Rainfall*

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1.0 Introduction

Tropical ecosystems are highly sensitive to variations in climate, particularly those influenced by large-scale climatic phenomena such as the El Niño-Southern Oscillation (ENSO) (Jamaludin & Nor, 2024). La Niña, the cold phase of ENSO, is characterized by intensified rainfall, which can significantly impact vegetation dynamics (Diem et al., 2018). In regions like Borneo, where tropical forests and ecosystems rely heavily on seasonal rainfall patterns, La Niña events may alter vegetation health, productivity, and growth (Suepa et al., 2016). Understanding these impacts is essential for managing biodiversity, assessing environmental changes, and predicting future climate variability. Borneo, the third-largest island in the world, lies at the heart of Southeast Asia's tropical belt and experiences a monsoon-driven climate (Sa'adi et al., 2024a). Its complex geography, varied topography, and rich biodiversity make it an ideal location for studying the effects of extreme climate events like La Niña (Zhang et al., 2024a). The Northeast monsoon (NEM), from November to March, brings substantial rainfall, while the Southwest monsoon (SWM), from May to September, is typically drier (Sa'adi et al., 2021). Consequently, La Niña's potential to enhance or redistribute rainfall during these monsoon periods could profoundly influence vegetation patterns across the island.

Despite the availability of remotely sensed vegetation data like the Normalized Difference Vegetation Index (NDVI) (Murakami et al., 2024) for monitoring vegetation health and dynamics, there is a significant gap in modeling the non-stationarity of climate influences on vegetation across Borneo. While NDVI provides a valuable understanding of vegetation vigor, productivity, and stress, its spatial and temporal responses to climate variability, particularly during La Niña events, vary due to local environmental factors such as soil moisture, topography, and land use. These localized influences create spatial heterogeneity that traditional modeling approaches often fail to capture. Previous work by Susilo et al. (2013), Tangang et al. (2017), Zhang et al. (2024b), and Pang et al. (2018) analyzed extreme rainfall during La Niña events using observational data and methods such as time series analysis, composite analysis, correlation analysis, and segmented regression. While these approaches provide a valuable understanding of past rainfall variability, their reliance on historical data and statistical methods may limit predictive capability. Additionally, composite analysis and segmented regression can introduce uncertainties, especially when small sample sizes or trend breakpoints are subjectively determined, potentially leading to less robust conclusions.

However, geographically Weighted Regression (GWR) (Yang et al., 2021) provides a more effective method by accounting for these local variations, making it ideal for examining the complex and non-stationary relationship between rainfall and vegetation in regions like Borneo. Previous studies have applied GWR to environmental processes in Borneo, including aboveground biomass distribution (Van der Laan et al., 2014) and fire density patterns (Wee et al., 2024). However, no studies have used GWR to examine regional rainfall-NDVI relationships. Given Borneo's hydroclimatic sensitivity, this study addresses a key gap by applying GWR to NDVI and rainfall data from the 2007 strong La Niña event, recognized for its significant impact and well-documented anomalies. Strong La Niña events are less common, occurring irregularly every 10 to 15 years, making the 2007 event one of the most recent and relevant strong cases for study. Analyzing a strong event enhances statistical clarity and reduces uncertainties in GWR analysis, enabling a more reliable assessment of rainfall-driven tropical greening across Borneo. The selection of the 2007 strong La Niña event ensures a meaningful understanding of climate-vegetation interactions under extreme climatic conditions rather than relying solely on recent occurrences.

By incorporating high-resolution NDVI data and rainfall estimates, this study offers a comprehensive assessment of the event's impact on vegetation dynamics in Borneo, emphasizing the critical role of spatially explicit models in understanding the effects of extreme climate events on tropical ecosystems. The findings of this study will contribute to improving the prediction of future climate impacts on tropical forests and other ecosystems in Southeast Asia, providing a deeper understanding of how La Niña events shape vegetation dynamics in the context of a changing climate. Furthermore, this work emphasizes the importance of incorporating spatially explicit data and techniques in ecological studies, ensuring that the unique environmental conditions of each region are properly accounted for in climate-vegetation models.

2.0 Study Area

Borneo, the third-largest island in the world, is located at the center of Southeast Asia and is characterized by its rich biodiversity and complex ecosystems (Allen & Allan, 2024) (Figure 1). The island is divided into three political regions: Malaysia (Sabah and Sarawak), Brunei, and Indonesia (Kalimantan), each with distinct geographical features. Borneo's tropical climate is classified into 'Wet and cold', 'Wet and hot', and 'Dry and hot' (Sa'adi et al., 2024a), which was heavily influenced by the monsoon system, with two primary monsoons: the NEM (from November to March) that brings heavy rainfall and the SWM (from May to September) that is typically drier. Borneo's diverse topography, which includes coastal plains, mountainous regions, and extensive tropical rainforests, creates a wide range of microclimates and ecological zones (Fujiki et al., 2017). This variability makes Borneo an ideal study area for investigating the impacts of climate phenomena such as La Niña on vegetation dynamics. The island's ecosystems are susceptible to changes in rainfall patterns, and its vast rainforests are home to unique species and critical ecosystem services (O'Brien et al., 2024). Understanding how extreme climate events like La Niña influence vegetation across such diverse landscapes is crucial for assessing the vulnerability of these ecosystems to climate variability and informing conservation and management strategies. The complex interaction between climate, topography, and land use in Borneo presents a valuable opportunity to explore spatially explicit models, such as GWR, to assess local variations in vegetation responses to changes in rainfall.

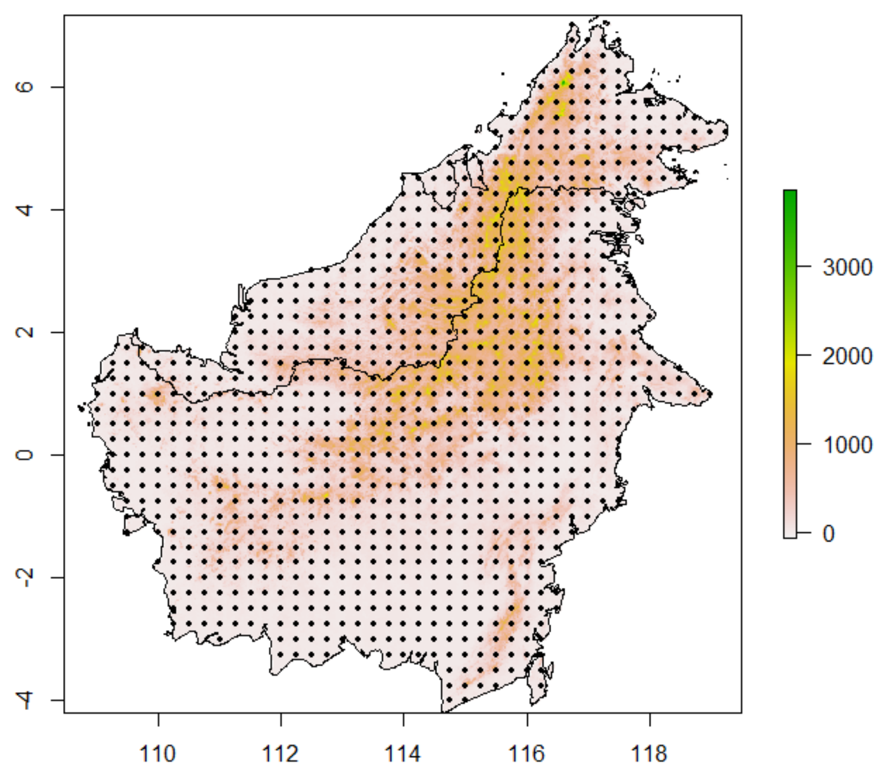

Figure 1. Study area of Borneo with 961 grid points of gridded-based satellite Climate Prediction Center Morphing technique (CMORPH) rainfall dataset and elevation based on Shuttle Radar Topography Mission (SRTM) at 90 m spatial resolution

3.0 Data and Sources

3.1 Gridded-based satellite CMORPH rainfall data

The CMORPH is a satellite-based dataset that provides high-resolution global rainfall estimates derived by morphing passive microwave (PMW) satellite observations across time and space to create a continuous, gridded rainfall product (Li et al., 2024). Developed by the National Oceanic and Atmospheric Administration (NOAA), CMORPH utilizes data from multiple geostationary and polar-orbiting satellites, ensuring comprehensive coverage, especially over data-scarce regions such as tropical rainforests. The technique combines PMW rainfall data with infrared (IR) observations to create a rainfall product with a resolution of 0.25° x 0.25° latitude/longitude and a 3-hour temporal resolution, providing fine-grained insights into precipitation patterns. For this study, the CMORPH dataset serves as the primary source of rainfall information across Borneo during the 2007 La Niña event. The high spatial and temporal resolutions of this dataset are particularly valuable for capturing localized rainfall events and evaluating rainfall impacts on vegetation across diverse microclimates and topographies in Borneo. In this context, CMORPH rainfall data enables a detailed assessment of the spatial and temporal relationships between precipitation and vegetation response, precisely measured through NDVI, which can reflect both immediate and cumulative vegetation responses to rainfall fluctuations.

While CMORPH provides valuable information, certain limitations are acknowledged in this study. The lack of direct ground validation can affect rainfall estimates from satellite data, especially in dense tropical regions where radar measurements are scarce or non-existent (Sabbaghi et al., 2024). Additionally, CMORPH may have reduced accuracy during intense, localized precipitation events due to inherent limitations in spatial resolution (Akbas & Ozdemir, 2024). These limitations may introduce biases in rainfall estimates, potentially affecting the accuracy of NDVI-rainfall relationships. The lack of ground validation could lead to over- or underestimation of rainfall, influencing the strength of correlations observed in the analysis.

Additionally, reduced accuracy during extreme rainfall events may impact the detection of peak NDVI responses, limiting the precision of spatial variability assessments. However, CMORPH remains a widely used dataset in hydrometeorological research for regions with limited in-situ rainfall observations (Dayal et al., 2024; Han et al., 2024), and its integration with GWR modeling enables this study to capture spatial variability in rainfall-vegetation relationships during an extreme climate event. The dataset's strengths in tracking rainfall across monsoon phases and complex topographies make it well-suited for understanding how large-scale climate phenomena influence tropical greening. However, this study did not conduct ground-based validation due to data availability constraints across multiple national jurisdictions, which pose challenges in accessing consistent and reliable station data. Future validation efforts could incorporate station-based rainfall measurements from regional meteorological agencies to enhance the accuracy of satellite-derived estimates and improve the reliability of the findings.

3.2 Normalized difference vegetation index (NDVI)

NDVI is a widely used remote sensing metric that measures vegetation health, density, and productivity by capturing variations in plant greenness (Zhu et al., 2024). Calculated from red and near-infrared (NIR) reflectance, it leverages that healthy vegetation absorbs visible red light for chlorophyll production and reflects NIR light. NDVI values range from -1 to +1, with higher positive values (0.2–0.9) indicating dense vegetation, values near zero representing sparse vegetation or bare soil, and negative values corresponding to non-vegetated surfaces like water or snow. In this study, NDVI data are used to examine vegetation responses to rainfall fluctuations during the 2007 strong La Niña event, a period of increased precipitation that potentially enhances tropical greening across Borneo's diverse ecological zones and elevation gradients. This research uses NDVI data from the MODIS satellite's Vegetation Indices Monthly L3 Global 1km product (MOD13A3), which provides monthly NDVI at a 1 km resolution (Yuan et al., 2024). This high resolution enables detailed analysis of vegetation responses across Borneo, capturing dynamics during key monsoon periods and responses to rainfall peaks from the 2007 La Niña event.

While NDVI is a valuable indicator of vegetation health, it has limitations: it primarily reflects green cover, which may overlook diverse vegetation types in layered forests or non-green biomass (Güler & Turgut, 2024). Atmospheric interference, sensor limitations, and mixed-pixel effects in complex landscapes can impact accuracy, and in dense tropical forests, canopy shadows and undergrowth may lead to underestimation of vegetation health (Zheng & Yu, 2024). Nonetheless, NDVI data provides critical insights into vegetation's spatial and temporal dynamics across Borneo during the 2007 La Niña event. Integrating NDVI into a GWR framework improves the understanding of spatially varied vegetation responses, enhancing insights into tropical ecosystems' reactions to large-scale climate anomalies (Wang et al., 2024). The Borneo climate, heavily influenced by La Niña events that often bring wetter conditions (Tan et al., 2021), was examined for the 2007 strong category event to assess the NDVI-rainfall relationship (Khor et al., 2021). NDVI was integrated with the duration of these events to measure vegetation productivity.

4.0 Methods

4.1 Test of spatial autocorrelation

Moran's I is a statistical measure used to assess spatial autocorrelation in geographic data (Vásquez et al., 2024). It quantifies the degree to which similar values cluster in space, offering insights into the spatial structure of a variable. The index is particularly useful in identifying whether nearby locations are more likely to exhibit similar characteristics (positive spatial autocorrelation) or dissimilar characteristics (negative spatial autocorrelation) or if the variable is randomly distributed across space (no spatial autocorrelation). The equation for Moran's spatial autocorrelation coefficient, denoted as *I*, is as follows:

$$I = \frac{\sum_{i=n}^{j} n(R_i - \bar{R})(R_j - \bar{R})}{\sum_{i=n}^{n} J(R_i - \bar{R})^2} \tag{1}$$

In this equation, n represents the total number of areas, J is the total number of joints, R_i and R_j are the rainfall depths in two adjacent areas, and $\bar{R}$ denotes the overall mean of rainfall. Positive Moran's I (I > 0) indicates that similar values, such as areas with high rainfall density, tend to cluster together. At the same time, negative Moran's I (I < 0) suggests dissimilarity with contrasting conditions like uniform rainfall patterns. A zero value (I = 0) implies no spatial correlation, indicating a random distribution across the study area. This measure is crucial for spatially explicit models, such as GWR, as it helps identify local patterns that differ from global trends. Moran's I provide valuable insights into spatial dependence, widely used in environmental studies, urban planning, and climate research (Ghalhari et al., 2016; Iriany et al., 2024; Javari, 2017). In this study, it was applied to assess rainfall spatial variability across Borneo.

4.2 Geographically weighted regression

GWR is a spatial analysis technique examining spatially varying relationships between variables (Debele & Beketie, 2024). Unlike traditional regression models, which assume uniform relationships across a region, GWR estimates local coefficients that vary depending on location, enabling the identification of spatially specific patterns (Ali et al., 2024). This method accounts for spatial non-stationarity, meaning the relationship between dependent and independent variables can vary across space. In GWR, each observation is weighted based on its proximity to other observations, with closer observations having a significantly greater influence on local regression estimates. The result is a set of location-specific parameters that provide a more detailed understanding of spatial dynamics. GWR is especially valuable in environmental and climate studies, where local factors like topography, land use, and climate conditions influence the interaction between variables (Khosravi et al., 2024). In this study, GWR was applied to assess the spatial variation in the relationship between rainfall and vegetation dynamics across Borneo during the 2007 La Niña event, allowing for a better understanding of how local environmental factors shape vegetation responses to climate variability. The GWR model, formulated as shown in equation 2, estimates location-specific coefficients that account for spatial heterogeneity in predictor-response relationships.

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_{1i} + \beta_2(u_i, v_i)x_{2i} + \cdots + \beta_k(u_i, v_i)x_{ki} + \epsilon_i \tag{2}$$

where:

y_i is the dependent variable at location i,

x_{1i}, x_{2i},… x_{ki} are the independent variables (predictors) at location i,

$\beta_0(u_i, v_i)$, $\beta_1(u_i, v_i)$,…, $\beta_k(u_i, v_i)$ are the local coefficients estimated at location *i,*

(u_i, v_i) represents the coordinates of location i in the spatial domain,

ϵ_i is the error term at location i,

The coefficients β_0, β_1,…, β_k vary across locations, reflecting spatial non-stationarity, which means that the relationship between the independent and dependent variables changes over space. The spatial distance between observations weights the estimation of these local coefficients. A kernel Gaussian function was used to assign weights, where closer observations have higher weights, and the influence of distant observations diminishes (Geniaux, 2024). This approach allows for a detailed exploration of spatial patterns in the data. The GWR model is typically fitted by minimizing a weighted sum of squared residuals, which incorporates the spatial weights based on the distance between locations. The result is a set of local regression coefficients that reveal how the relationships between variables differ across space, offering a deeper understanding of spatially variable processes such as those found in environmental and climate studies.

4.3 Model comparison

The Brunsdon, Fotheringham, and Charlton (2002) ANOVA method is used in GWR to test whether the spatially varying relationships between the dependent and independent variables are statistically significant. The ANOVA statistic compares the fit of the local GWR model with that of the global ordinary least squares (OLS) model. The equation for the ANOVA statistic is given by:

$$F = \frac{\frac{RSS_{global} - RSS_{local}}{p}}{\frac{RSS_{local}}{(n-p-1)}} \tag{3}$$

where RSS_{global} and RSS_{local} are the residual sum of squares for the global and local models, respectively; p is the number of parameters in the model (including the intercept), and n is the number of observations. A significant value for F (indicating a small p-value) suggests that the GWR model better fits the global model, highlighting the importance of spatially varying relationships in the data.

4.4 Evaluation of predicted pattern

To evaluate the predictive performance of the GWR model in predicting NDVI, three statistical indices were utilized: the Mean Absolute Error (MAE) (see equation 4), Root Mean Square Error (RMSE) (see equation 5), and percent bias (PBIAS) (see equation 6). Furthermore, spatial maps of observed and predicted NDVI values were generated to assess the model's accuracy across the study area visually.

$$MAE = \frac{1}{N} \sum_{t=1}^{N} [z_t^* - z_t] \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} [z_t^* - z_t]^2}{N}} \tag{5}$$

$$PBIAS = \frac{\sum_{i-1}^{n} (O_i - M_i)}{\sum_{i-1}^{n} O_i} \times 100 \tag{6}$$

5.0 Results and Discussion

5.1 Spatial distribution of rainfall and NDVI in Borneo

Moran's I assess spatial autocorrelation, indicating whether variable values are clustered, dispersed, or randomly distributed. In this analysis, Moran's I was calculated for monthly rainfall data during the 2007 strong La Niña event across Borneo, with values ranging from 0.012 to 0.034, indicating a low level of positive spatial autocorrelation. Positive values suggest rainfall tends to cluster geographically, with statistically significant p-values supporting spatial dependence. The highest Moran's I value of 0.034 occurred in September, likely reflecting seasonal influences. The analysis highlights significant spatial clustering of rainfall, emphasizing the importance of spatial factors in ecological studies. The spatial distribution of monthly rainfall in Borneo during the 2007 intense La Niña event shows significant variation, as shown in Figure 2. In January, rainfall ranges from 300 to 700 mm, particularly in the north-western coast of Sarawak, as well as in the southwest, southern, central, and northeastern regions.

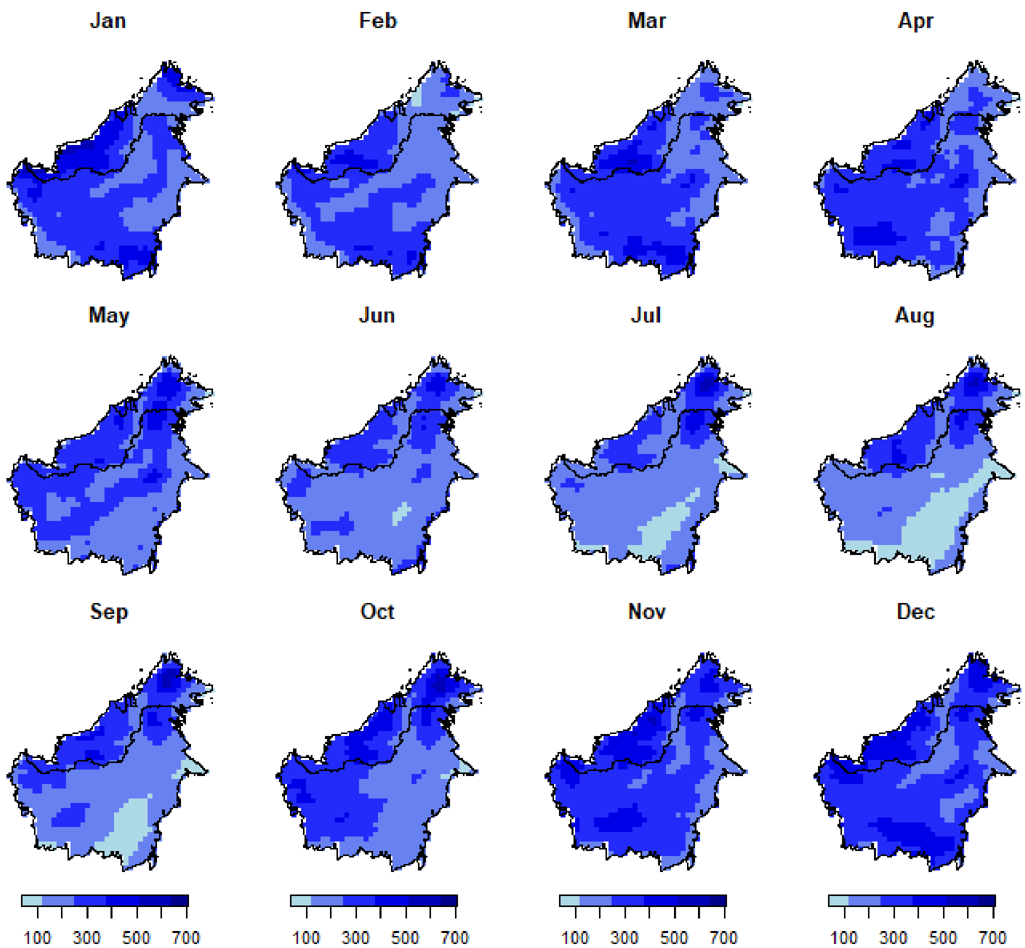

Figure 2. Spatial distribution of monthly rainfall (mm) in Borneo during the 2007 intense La Niña event

February sees a slight decrease, but rainfall remains substantial, ranging from 300 to 700 mm. March follows a similar pattern. In April, rainfall drops to 300–500 mm, with coastal areas receiving slightly less. May shows further reductions, particularly in central and southern regions (200–500 mm). June sees an increase, with values returning to 300–700 mm, particularly in northern and central areas. July typically experiences higher rainfall in the north, ranging from 300 to 700 mm. August and September show similar trends, with high rainfall in the north. October sees an increase, particularly in central regions, reaching 700 mm. November and December experience the highest rainfall (500–700 mm), marking the peak of the La Niña effect. This aligns with Zhang et al. (2024a), who reported that extreme precipitation in Borneo typically occurs from late December to mid-January during La Niña, driven by a dipole anomalous vertical motion pattern over the Maritime Continent (MC) and tropical Pacific, influenced by seasonal changes in sea surface temperature (SST) in the eastern equatorial Pacific.

The monthly NDVI in Borneo during the 2007 intense La Niña event shows a consistent spatial distribution throughout the year, with NDVI values generally ranging from 0.4 to 0.8 (Figure 3). In January, the NDVI is relatively high across most areas, indicating healthy vegetation, with values predominantly between 0.6 and 0.8, particularly in the central and northern regions. February and March maintain similar patterns, with dense vegetation across Borneo, as reflected by NDVI values that are mostly above 0.6. In April, there is a slight decrease in NDVI values, with some regions showing values closer to 0.4, especially in southern and coastal areas. From May to July, there is a stabilization in NDVI values across the island, with the central regions consistently displaying high values of 0.6 to 0.8, while the peripheral areas show slightly lower values, ranging from 0.4 to 0.6. Kemarau and Eboy (2022) found that during the late 2017/18 La Niña event, improved Vegetation Health Index (VHI) values reflected healthier vegetation, as increased rainfall alleviated drought and enhanced plant health by providing adequate moisture for photosynthesis. From August to October, NDVI values indicate a healthy vegetation cover, with most areas exhibiting values ranging from 0.6 to 0.8. During this period, there is little spatial variability across Borneo, indicating widespread vegetation growth likely supported by the wet conditions of the La Niña event. November and December exhibit similar values, with most Borneo regions showing NDVI values between 0.6 and 0.8, particularly in the central and northern areas, indicating robust vegetation health across these regions. The La Niña event likely contributed to these conditions by supporting abundant rainfall and vegetation growth across the island. Overall, the high NDVI values throughout the year reflect lush and dense vegetation in Borneo, with slight fluctuations in peripheral regions and lower values along the southern and coastal areas. The findings support the work of Kemarau and Eboy (2022), which highlighted that different districts in Sarawak experienced varying levels of vegetation health during La Niña.

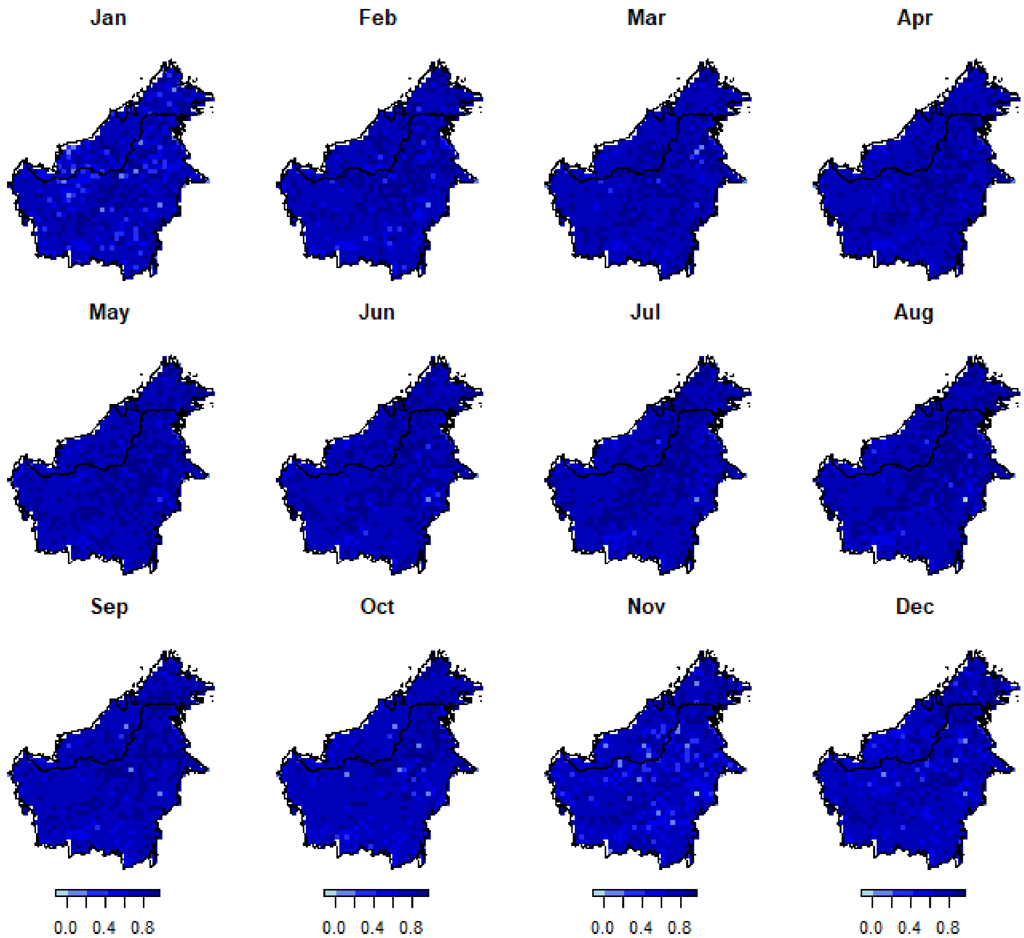

Figure 3. Spatial distribution of monthly NDVI in Borneo during the 2007 intense La Niña event

5.2 Spatial analysis of rainfall-NDVI relationship using GWR

The Brunsdon, Fotheringham, and Charlton (2002) ANOVA results for each monthly GWR model test the spatial non-stationarity of the relationship between rainfall and NDVI for each month during the 2007 La Niña event. Each test compares the OLS model, which assumes a constant relationship across the study area, to the GWR model, which allows for spatially varying coefficients (Table 1). For La Niña 2007, the F-statistic, degrees of freedom (df1 = 959 and df2), p-values, and residual sum of squares (SS) are provided for both the OLS and GWR models. In each monthly test, the results indicate a statistically significant improvement in fit for the GWR model compared to the OLS model. This suggests that the relationship between rainfall and NDVI varies across the study region, supporting the hypothesis of spatial non-stationarity. For most months, the F-statistic is greater than 1, and the p-values are below 0.05, indicating that the GWR model explains a significantly more significant portion of the variance in NDVI than the OLS model. The residual sums of squares for the GWR model are consistently lower than those of the OLS model across all months, reflecting an improved fit. The spatially varying coefficients in the GWR model likely capture localized variations in the relationship between rainfall and NDVI, which the global OLS model cannot. Previous work by Kashki et al. (2021) also found that GWR outperformed OLS in modeling the spatial distribution of Land Surface Temperatures (LSTs) in Shiraz, effectively capturing the localized variations in how geographic factors influence LST across the city. Another study by Khalid, Shamim, and Ahmad (2024) also demonstrates that GWR outperforms OLS by accounting for spatial non-stationarity, allowing it to capture localized variations in the relationship between LST and its predictors. This highlights GWR's ability to model local patterns and provide a more accurate representation of spatial dynamics in heterogeneous regions.

Table 1. Summary of GWR results across all months for 2007 strong La Niña events

Month	Bandwidth	F-Statistic	df2	p-value	SS OLS Residuals	SS GWR Residuals
Jan	0.01127	1.2368	854.83	0.0007269	27.24028	22.02405
Feb	0.00828	1.3204	833.55	0.00001835	13.63874	10.32937
Mar	0.01667	1.1921	879.75	0.003973	10.362201	8.692647
Apr	0.00520	1.3929	804.89	0.000000575	7.093546	5.092679
May	0.00521	1.4196	806.16	1.356E-07	8.056353	5.675174
Jun	0.01251	1.2324	862.85	0.0008481	9.370429	7.60317
Jul	0.00518	1.4586	808.47	1.499E-08	7.959187	5.456546
Aug	0.01311	1.2301	868.2	0.0009172	9.659869	7.852958
Sep	0.00729	1.3583	828.84	0.000002849	9.337822	6.874647
Oct	0.00522	1.4287	803.12	8.477E-08	12.912359	9.037551
Nov	0.01872	1.1223	895.82	0.03986	24.21611	21.57814
Dec	0.00476	1.408	787.32	3.053E-07	16.35751	11.6172

Summary: The table showed variations in bandwidth, F-statistics, and p-values. The consistently low p-values indicate statistically significant relationships. At the same time, the reduction in residual sums of squares (SS OLS vs. SS GWR) highlights the improved model fit achieved by incorporating spatial variability. Notably, the highest F-statistics are observed in April, May, and

July, suggesting more substantial spatial heterogeneity in the rainfall-NDVI relationship during these months.

The results of the GWR analyses for the 2007 strong La Niña events are summarized in Table 2, detailing model fit statistics for each month. For each monthly model, several key metrics were observed, including the Akaike Information Criterion (AIC), the corrected AIC (AICc), Quasi-global R^2, residual sum of squares (RSS), and sigma, which offer insights into model performance and spatial variability. In October, the GWR model displayed the lowest AIC (237.38) and AICc (237.41), with a high Quasi-global R^2 of 0.3125, indicating the best model fit among all months. This suggests that the spatially varying relationship between rainfall and NDVI was most effectively captured this month, with an RSS of 0.253882 and a sigma of 0.5299, indicating minimal residual error. September and December also exhibited strong model performance with Quasi-global R^2 values of 0.2744 and 0.2899, respectively, and relatively low RSS values, underscoring significant spatial non-stationarity in the rainfall-NDVI relationship during these months.

Conversely, the GWR models for June and July showed the weakest model fit, with the lowest Quasi-global R^2 values (0.1453 in June and 0.1369 in July) and relatively higher AIC values (264.31 in June and 269.76 in July), suggesting that spatial variation in the rainfall-NDVI relationship was less pronounced during the mid-year. Notably, sigma values were also higher in these months (0.6084 for June and 0.5954 for July), indicating greater residual variance than other months. Overall, the GWR analysis highlights that the spatial variability in rainfall's influence on NDVI is not constant throughout the year. High Quasi-global R^2 values and lower RSS values in the wet season months, particularly October, September, and December, reflect more significant spatially clustered responses of NDVI to rainfall during these periods, likely due to increased vegetation response to La Niña-induced rainfall in tropical regions. Consistent with Hu and Xu (2019), the study shows that GWR captures spatial variability in relationships between dependent and independent variables, enabling localized analysis. GWR models demonstrated higher adjusted R^2 values, indicating a better data fit, along with smaller AIC values and RSS, reflecting improved accuracy in data representation.

Table 2. Results from the GWR analyses for each month for 2007 La Niña events

Month	AIC	AICc	Quasi-global R^2	RSS	Sigma
January	257.19	257.21	0.1834	0.320052	0.5544
February	250.77	250.8	0.2257	0.290086	0.5386
March	249.7	249.73	0.2386	0.298209	0.5423
April	252.67	252.7	0.2124	0.309163	0.5535
May	259.58	259.61	0.1908	0.346713	0.5582
June	264.31	264.34	0.1453	0.367008	0.6084
July	269.76	269.79	0.1369	0.370856	0.5954
August	254.16	254.19	0.2064	0.296882	0.553
September	242.91	242.94	0.2744	0.262588	0.5318
October	237.38	237.41	0.3125	0.253882	0.5299
November	259.82	259.85	0.1316	0.331155	0.5641
December	245.87	245.9	0.2899	0.278525	0.5461

Summary: The table highlights variations in model performance across different months. The quasi-global R^2 values indicate the strength of the rainfall-NDVI relationship, with the highest values observed in October (0.3125) and December (0.2899), suggesting a stronger spatial correlation during these months. The lowest R^2 values in June (0.1453) and November (0.1316) reflect weaker model performance, likely due to seasonal variations in vegetation response. Additionally, lower AIC and AICc values in October and September indicate a better model fit than in other months.

5.3 Spatial patterns of the NDVI-rainfall relationship

The monthly pattern of local R^2 values in Borneo reflects the influence of monsoonal rainfall on vegetation dynamics, exhibiting distinct seasonal variations across the NEM (November–March), SWM (May–September), and the inter-monsoon periods (April and October) (Figure 4). During the NEM, the primary rainy season, the relationship between rainfall and NDVI is strongest. The maximum R^2 values range from 0.27 in November to 0.54 in February, with December peaking at 0.74. Higher correlations are primarily observed in central and southern Borneo, indicating that rainfall plays a key role in driving vegetation growth during this period. According to Takamura et al. (2023), the net ecosystem productivity in Bornean rainforests reaches its peak during La Niña events. This increase indicates that vegetation becomes notably more productive, likely driven by climatic conditions that promote enhanced photosynthesis and growth. However, some northern areas exhibit lower correlations, likely due to differences in monsoonal influence, topography, vegetation types, land cover, or soil moisture retention capacities. Despite the overall strong relationship, the minimum R^2 values remain low (0.02–0.05), indicating that other environmental factors influence vegetation response in certain regions.

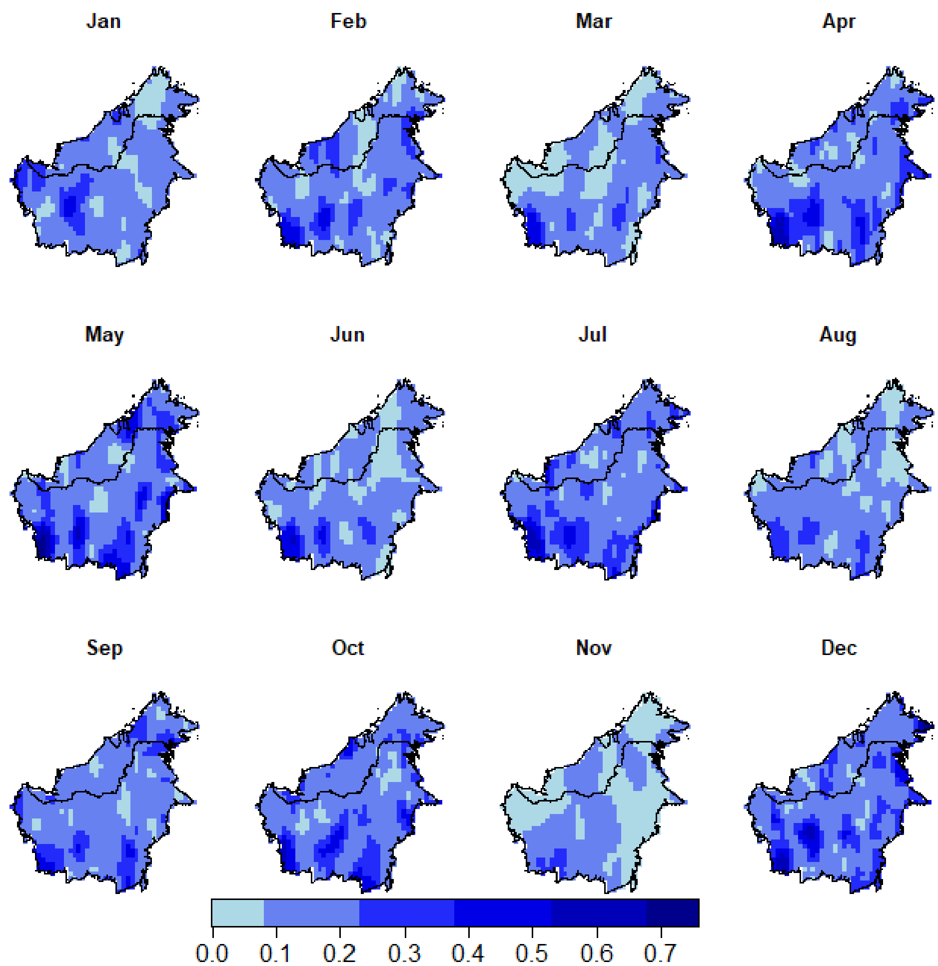

Figure 4. Spatial distribution of local R^2 patterns for the 2007 La Niña event

The inter-monsoon periods (April and October) mark a transition in the rainfall-NDVI relationship. Maximum R^2 values remain relatively high, reaching 0.67 in April and 0.64 in October, suggesting that increased convective rainfall during these months considerably influences vegetation. Moderate to high correlations are observed mainly in southern and western Borneo, likely due to residual soil moisture from the preceding wet season sustaining vegetation activity. The minimum R^2 values (0.03–0.04) are slightly higher than in the dry season, reflecting moderate spatial variability. During the SWM, characterized by drier conditions, the relationship between rainfall and NDVI weakens. However, the high maximum R^2 value of 0.76 in May may be attributed to the residual influence of the preceding inter-monsoon period, where increased convective rainfall sustains vegetation activity. Then, maximum R^2 values decline to their lowest in August (0.36), slightly recovering in September (0.49). The lowest R^2 values (0.00–0.04) occur during this period, particularly in northern and eastern Borneo, indicating a weakened rainfall-NDVI relationship in the dry season. Sa'adi et al. (2024a) suggest that monsoon effects vary across Borneo's distinct climate zones. In particular, the 'Dry and Hot' zone in the southern region receives comparatively less rainfall, which diminishes the impact of La Niña in that area. Here, Borneo's central mountain range, including the Crocker Range in Sabah and the highlands of East Kalimantan, acts as a barrier to moist air masses. As winds rise over these highlands, orographic lifting increases rainfall on the windward slopes, while the descending air on the leeward side (northern Sabah and East Kalimantan) undergoes adiabatic warming, reducing moisture and limiting rainfall. Land cover also plays a key role in this pattern.

This reduction also suggests that vegetation growth may be influenced by soil moisture availability or by deeper-rooted plants accessing stored water, rather than relying solely on immediate rainfall. The northern and eastern regions of Borneo contain a mix of degraded forests and plantation areas, which have lower soil moisture retention and vegetation resilience compared to dense tropical rainforests (Shiraishi et al., 2023). In contrast, western Borneo, with its more extensive forest cover, retains higher moisture levels, supporting a stronger NDVI response to rainfall. Additionally, peatlands and riparian zones in western Borneo sustain vegetation activity even in drier months (Omar et al., 2022). Meanwhile, drier upland areas in northern Sabah and East Kalimantan experience more distinct seasonal fluctuations in NDVI. The spatial distribution pattern indicates that the influence of rainfall on vegetation health and density, as represented by NDVI, is not uniform across Borneo. The overall results highlight the dominant influence of the NEM on vegetation, particularly in December, when the highest maximum R^2 value of 0.74 is observed. These seasonal dynamics highlight the primary role of rainfall in driving vegetation changes across Borneo, while also emphasizing the influence of additional environmental conditions on shaping the rainfall-NDVI relationship. This analysis underscores the spatial non-stationarity of the rainfall-NDVI relationship during the 2007 strong La Niña event, with more pronounced effects in specific regions and times of the year.

The spatial distribution of rainfall coefficients from the GWR analysis for the 2007 strong La Niña event reveals distinct monthly variations across Borneo, capturing how NDVI responds to rainfall increases in different regions (Figure 5). Rainfall coefficients range from -0.002 to 0.001, showing spatial and temporal variations in the rainfall-NDVI relationship. Positive coefficients indicate areas where increased rainfall boosts NDVI, suggesting higher vegetation responsiveness. Negative coefficients suggest that rainfall increases do not enhance or only slightly reduce NDVI, possibly due to limiting factors. The maps show notable positive coefficients across Borneo, reaching a value of 0.001. This pattern suggests vegetation in these regions was exceptionally responsive to La Niña-induced rainfall. Supporting this, O'Brien et al. (2024) observed that excessive rain in lowland, aseasonal tropical forests in Malaysia's tropical region can hinder tree growth and survival, likely because of increased vulnerability to prolonged waterlogging.

In contrast, certain localised areas consistently exhibit low or negative coefficients throughout the year, indicating regions where increased rainfall correlates with a slight reduction or lack of response in NDVI. This pattern varies notably across months. Negative coefficients are relatively sparse at the beginning of the year, appearing only in isolated areas in January and February, primarily in the easternmost part and the central north-western enclave in Miri, Sarawak, and Brunei. This might be due to saturation due to flood occurrence (Isia et al., 2023; Taris et al., 2019) in this area caused by the co-occurrence of the Borneo vortex and cold surge during the peak of NEM (Purwaningsih et al., 2022). By March, these areas will have expanded, particularly in the central-eastern region of Borneo, suggesting a minor inverse relationship between rainfall and vegetation response. Ariska et al. (2024) indicate that areas consistently showing a negative relationship may be linked to the Niño3 region and the South Pacific convergence zone. Here, warmer sea surface temperatures (SST) in the warm pool area are associated with decreased rainfall over Indonesia.

In the mid-year months of June and July, negative coefficients become more prominent in the southern regions, indicating that rainfall during this period has a limited influence on NDVI, possibly due to the influence of geographical climate zones and monsoonal factors that restrict vegetation response. In August, there is a reduction in these negative zones, which re-emerge in localized areas by October, primarily in central Borneo, and persist through November in northern and central areas. December shows scattered negative coefficients across northern and southern regions, suggesting a continued lack of vegetation response to rainfall in certain parts of the island towards the end of the year due to flooding and saturation. This pattern highlights how the impact of rainfall on vegetation can be regionally constrained during the La Niña event, with varying seasonal and geographical limitations on vegetation's responsiveness to rainfall across Borneo. Overall, this analysis highlights the spatially and temporally varying influence of rainfall on NDVI during the 2007 strong La Niña event, with the most pronounced positive relationships observed in early and mid-year months across northern and central regions of Borneo.

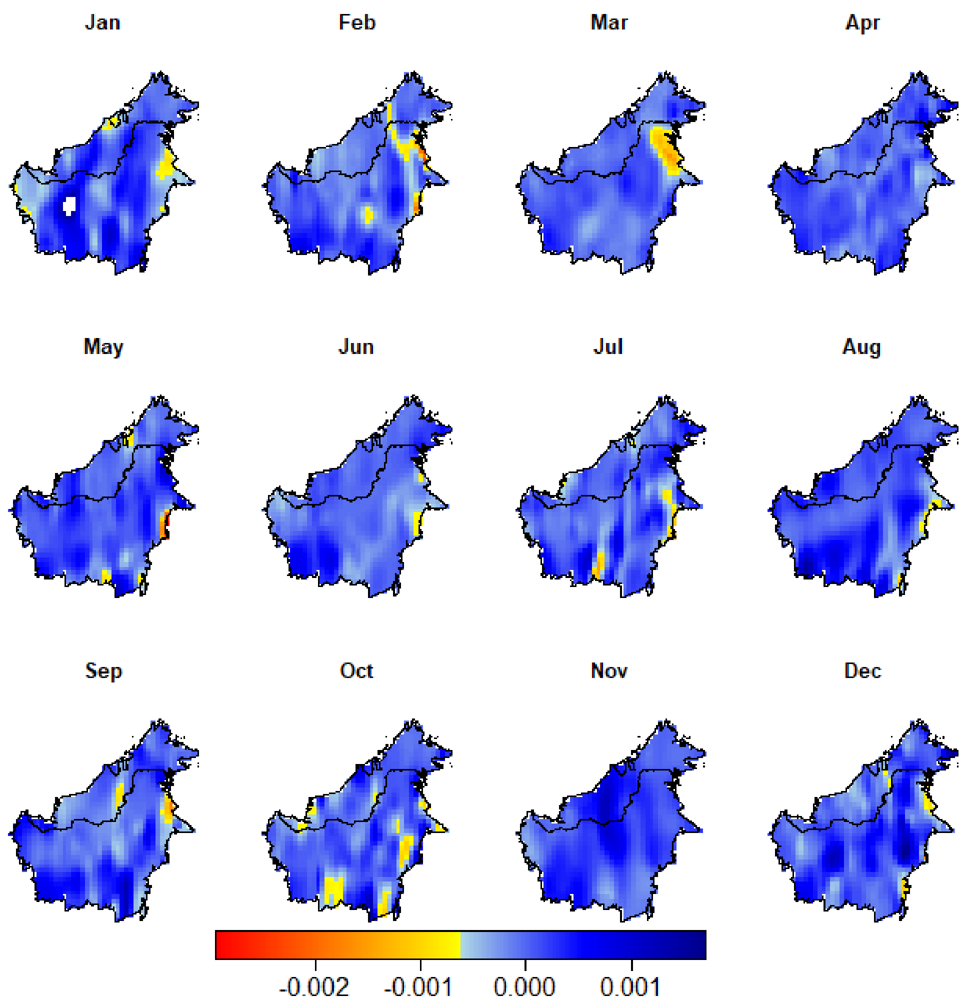

Figure 5. Rainfall coefficients during the 2007 La Niña event. The coefficients related to rainfall illustrate the extent of change in NDVI for a spatial unit with a corresponding increase in a spatial unit of rainfall

5.4 Performance of the predicted pattern

The predicted NDVI values for the 2007 intense La Niña event generally show a strong performance in capturing the regional vegetation response, particularly the enhanced greenness associated with La Niña's wetter conditions (Figure 6). The model's predictions demonstrate high NDVI values across Borneo, with ranges from 0.5 to 0.9. This aligns well with the expected increase in vegetation vigor due to the elevated rainfall during a La Niña year. This suggests that the model effectively captures seasonal and spatial variations in NDVI influenced by precipitation. However, there are a few areas where the predictions could potentially under- or overestimate NDVI in certain months. For instance, while the northern and central parts of Borneo show higher NDVI values in May, October, and December, the model may not fully capture localized fluctuations in vegetation health that can occur due to factors such as land use, soil type, or extreme rainfall variability.

Furthermore, the relatively uniform NDVI distribution in certain months, such as February and November, may overlook smaller-scale variations in vegetation, especially in more heterogeneous landscapes. Overall, the predicted NDVI values perform well in reflecting broad seasonal vegetation dynamics across Borneo during La Niña conditions, particularly in capturing the peak vegetation months. However, the model's spatial resolution and focus on rainfall as a primary predictor may limit its ability to capture finer-scale ecological variations, suggesting potential areas for improvement by incorporating additional variables or higher-resolution data.

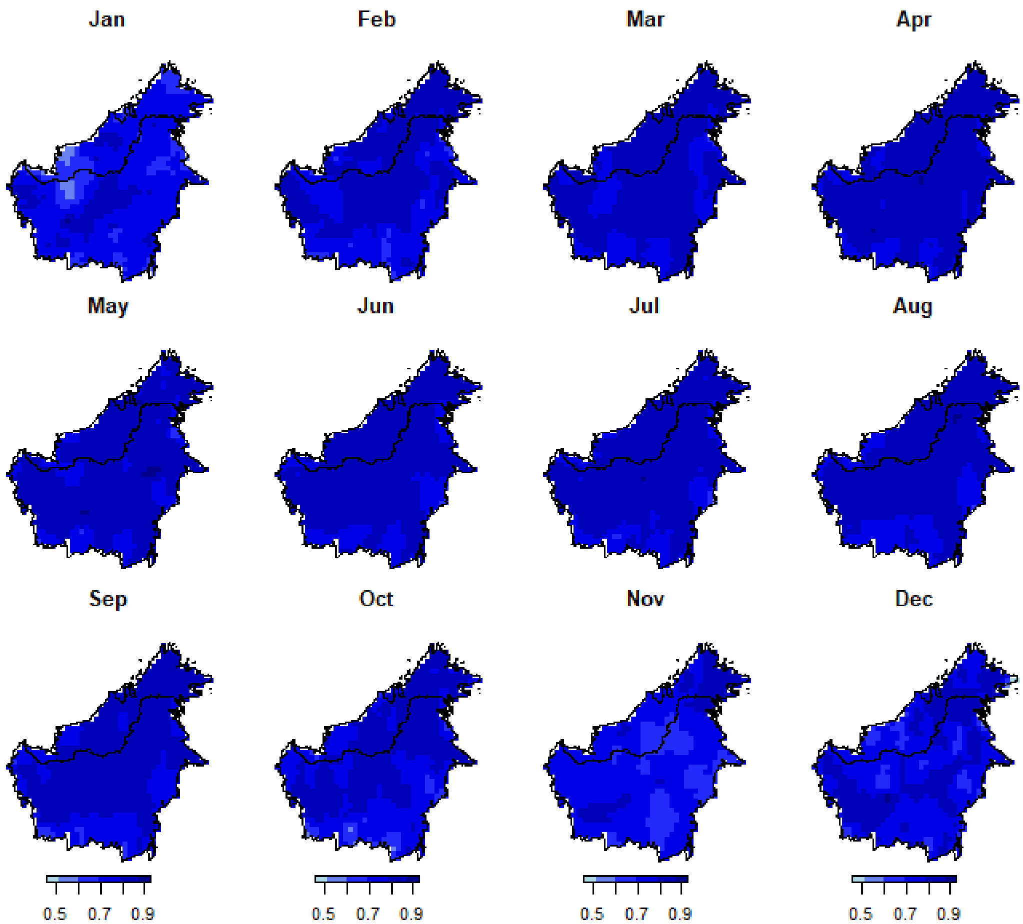

Figure 6. Spatial distribution of predicted NDVI during the 2007 La Niña event

The statistical evaluation of the observed NDVI against the predicted NDVI, measured using MAE, RMSE, and PBIAS, provides insights into the model's performance across each month of the year (Table 3). The MAE values indicate that the average error between observed and predicted NDVI values ranges from 0.049 to 0.112. April and May have the lowest MAE (0.049), suggesting that the model is most accurate in these months. January and November have the highest MAE values, at 0.112 and 0.111, respectively, indicating slightly higher prediction errors during these months. RMSE, which emphasizes larger errors, varies from 0.073 to 0.151 across months. Similar to MAE, the lowest RMSE is observed in April (0.073), indicating that the model performs best in April. The highest RMSE is observed in January (0.151), indicating that prediction accuracy decreases during this month, which may be attributed to more variable NDVI responses to environmental factors early in the year. PBIAS values represent the model's tendency to over- or underestimate NDVI. Most months exhibit a positive PBIAS, indicating a general tendency for the model to overpredict NDVI values slightly. August has the highest PBIAS (0.353), followed by June (0.331) and March (0.268), suggesting notable overestimations in these months.

In contrast, November and December exhibit the lowest PBIAS (0.091), indicating minimal bias and relatively balanced prediction performance in these months. The model performs reasonably well, with moderate MAE and RMSE values and relatively low PBIAS values in many months. The tendency for overestimation in certain months, especially during mid-year, may suggest that the model could benefit from adjustments to account for seasonal or environmental factors specific to these periods. The months with lower errors (such as April, May, November, and December) indicate stronger predictive performance, possibly due to more stable NDVI patterns during these months. This analysis suggests areas for model refinement, mainly to reduce overestimation in mid-year months.

Table 3. Statistical evaluation of the observed NDVI against predicted NDVI

Month	MAE	RMSE	PBIAS
Jan	0.112	0.151	0.161
Feb	0.073	0.104	0.158
Mar	0.061	0.095	0.268
Apr	0.049	0.073	0.254
May	0.049	0.077	0.107
Jun	0.056	0.089	0.331
Jul	0.050	0.075	0.218
Aug	0.058	0.090	0.353
Sep	0.055	0.085	0.243
Oct	0.061	0.097	0.227
Nov	0.111	0.150	0.091
Dec	0.080	0.110	0.091

6.0 Conclusion

This research provides an in-depth evaluation of NDVI dynamics during the 2007 strong La Niña event across Borneo, focusing on the spatial relationship between rainfall and vegetation response. Using GWR, this study assesses the spatial distribution of local R^2, rainfall coefficients, and predicted NDVI, illustrating how changes in rainfall impact vegetation greenness. The findings reveal significant spatial variability, with certain areas exhibiting a stronger response to rainfall fluctuations, reflecting the sensitivity of vegetation in these regions to La Niña-induced rainfall patterns. The statistical assessment of model performance, using MAE, RMSE, and PBIAS, demonstrated strong predictive accuracy in the earlier months of the year, particularly in April and May, where both MAE and RMSE values were relatively low, indicating minimal deviation from observed values. However, the model showed a trend of overestimating NDVI during the peak SWM months (June to August), as evidenced by elevated PBIAS values, suggesting that the model may not fully capture the complexities of vegetation response to extreme drier conditions during these periods. The spatial distribution maps for predicted NDVI further emphasize the areas with higher rainfall coefficients, illustrating how certain regions are more likely to experience vegetation greening with increased rainfall.

These findings have practical implications for land management and conservation in Borneo. By identifying regions more resilient or vulnerable to climate variability, policymakers and environmental agencies can develop targeted conservation strategies, prioritize reforestation efforts, and enhance ecological resilience in areas prone to extreme climate events. Additionally, findings from this study can guide land-use planning to minimize the impact of climate-induced vegetation shifts on agriculture, forestry, and biodiversity conservation. This study helps flood adaptation in Borneo by identifying regions where vegetation is highly sensitive to rainfall fluctuations, particularly during La Niña events associated with increased rainfall and flooding. For example, in flood-prone areas like the Sarawak River Basin in north western Borneo (Ghenim & Megnounif, 2023), the study's findings on NDVI-rainfall relationships can help determine zones where vegetation loss is likely due to prolonged flooding. This can guide reforestation efforts with flood-resistant plant species, such as mangroves and deep-rooted trees, to enhance natural flood buffers (Tasnim et al., 2023). Additionally, areas showing strong NDVI response to rainfall can be prioritized for sustainable land-use planning, reducing deforestation that exacerbates flood risks. By integrating these findings with flood early warning systems, local authorities can improve watershed management strategies, ensuring better preparedness for extreme rainfall events.

Furthermore, the application of GWR in this study demonstrates its potential for predicting future climate impacts under changing climate scenarios. By integrating projected rainfall data from climate models (Sa'adi et al., 2024b), GWR can be employed to assess how vegetation dynamics may respond to future climate variability, helping to refine adaptation strategies. This approach can aid in developing proactive policies to mitigate the adverse effects of climate change on ecosystems and agricultural productivity in Borneo. Overall, this study underscores the utility of NDVI as a measure of vegetation response to climatic events and highlights the need for further refinement of predictive models to improve their accuracy during extreme rainfall periods. Future research should incorporate additional environmental variables, such as soil moisture and land cover dynamics, to enhance model performance and ensure more robust predictions of vegetation responses under future climate scenarios. These advancements will support more effective adaptation and resilience strategies, particularly in ecologically sensitive and climate-vulnerable regions like Borneo.

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